A Novel Approach for Spectral Imagery Based on Edge Detector using Sparse Spatio-Spectral Masks

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Abstract: This paper describes a computational approach to edge detection. The success of the approach depends on the definition of a comprehensive set of goals for the computation of edge points. These goals must be precise enough to delimit the desired behavior of the detector while making minimal assumptions about the form of the solution. We define detection and localization criteria for a class of edges, and present mathematical forms for these criteria as functional on the operator impulse response. A third criterion is then added to ensure that the detector has only one response to a single edge. We use the criteria in numerical optimization to derive detectors for several common image features, including step edges. On specializing the analysis to step edges, we find that there is a natural uncertainty principle between detection and localization performance, which are the two main goals. With this principle we derive a single operator shape which is optimal at any scale. In the presented examples, the required operations per pixel are reduced by a factor of 71 with respect to those required by the MCG edge detector. The optimal detector has a simple approximate implementation in which edges are marked at maxima in gradient magnitude of a Gaussian-smoothed image. The results demonstrate that the proposed algorithms outperform the MCG and HySPADE edge detectors in accuracy, especially when isoluminant edges are present by requiring only a few bands as input to the spatio-spectral operator, the algorithms enable significant levels of data compression in band selection. We extend this simple detector using operators of several widths to cope with different signal-to-noise ratios in the image.

Keywords: Edge Detection, Isoluminant Edge, Classification, Multicolor Edge Detection, Spatio-Spectral Mask, Spectral Ratios.

I. INTRODUCTION

Edge detectors of some kind, particularly step edge detectors, have been an essential part of many computer vision systems. The edge detection process serves to simplify the analysis of images by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries. There is certainly a great deal of diversity in the applications of edge detection, but it is felt that many applications share a common set of requirements. These requirements yield an abstract edge detection problem, the solution of which can be applied in any of the original problem domains. We should mention some specific applications here. The Binford-Horn line finder used the output of an edge detector as input to a program which could isolate simple geometric solids. More recently the model-based vision system ACRONYM used an edge detector as the front end to a sophisticated recognition program. Shape from motion can be used to infer the structure of three-dimensional objects from the motion of edge contours or edge points in the image plane. Several modern theories of stereo vision assume that images are preprocessed by an edge detector before matching is done. Beattie describes an edge-based labeling scheme for low-level image understanding. Finally, some novel methods have been suggested for the extraction of three dimensional information from image contours, namely shape from contour and shape from texture.

In all of these examples there are common criteria relevant to edge detector performance. The first and most obvious is low error rate. It is important that edges that occur in the image should not be missed and that there be no spurious responses. In all the above cases, system performance will be hampered by edge detector errors. The second criterion is that the edge points be well localized. That is, the distance between the points marked by the detector and the "center" of the true edge should be minimized. This is particularly true of stereo and shape from motion, where small disparities are measured between left and right images or between images produced at slightly different times. In this paper we will develop a mathematical form for these two criteria which can be used to design detectors for arbitrary edges. We will also discover that the first two criteria are not "tight" enough, and that it is necessary to add a third criterion to circumvent the possibility of multiple responses to a single edge. Using numerical optimization, we derive optimal operators for ridge and roof edges. We will then specialize the criteria for step edges and give a parametric closed form for the
solution. In the process we will discover that there is an uncertainty principle relating detection and localization of noisy step edges, and that there is a direct tradeoff between the two. One consequence of this relationship is that there is a single unique "shape" of impulse response for an optimal step edge detector, and that the tradeoff between detection and localization can be varied by changing the spatial width of the detector. Several examples of the detector performance on real images will be given.

The sparse Spatio-spectral mask used in the SRC and the ASRC algorithms is an important mark of distinction from the MCG-based edge detector and other multispectral edge detection algorithms. A second key distinctive mark of the proposed two algorithms is that they are not derivative-based: edge detection is effected by matching an edge signature rather than by measuring the gradient's magnitude. Moreover, the application of spectral ratios to define multispectral operators for edge detection is a novel and a previously unexplored research direction. However, spectral ratios have been previously used in many techniques for quantitative vegetation monitoring, regional seismic discrimination and deblurring of noisy multichannel images. The paper is organized as follows. In Section II we present the Existing and Proposed Systems. In Section III we present results of applying the algorithm to real data from the Airborne Hyper spectral Imager (AHI) and a quantum dots-in-a well (DWell) mid-infrared (IR) imager and compare the performance to those resulting from the Canny, MCG and HySPADE edge detectors. Our conclusions are presented in Section V.

II. EXISTING AND PROPOSED SYSTEMS

A. Existing System

The extension of gray-scale edge detection to multicolor images has followed three principal paths. A straightforward approach is to apply differential operators, such as the gradient, separately to each image plane and then consolidate the information to obtain edge information identified several key drawbacks of such a straightforward approach. First, edges can be defined by combinations of different image planes and these edges may be missing in some of the image planes. Second, processing image planes separately disregards potential correlation across image planes. Third, integration of information from separate image planes is not trivial and is often done in an ad hoc manner. Moreover, in cases when an edge appears only in a subset of image planes, there are no standard ways to fuse the information from different planes. In recent years, new gray-scale algorithms were presented in the community.

B. Proposed System

The results demonstrate that the proposed algorithms outperform the MCG and HySPADE edge detectors in accuracy, especially when isoluminant edges are Present. We present the SRC and the ASRC algorithms. We present results of applying the algorithm to real data and compare the performance to those resulting from the Canny, MCG and HySPADE edge detectors. We present a complexity analysis of the algorithms. The dramatic reduction in the number of operations with respect to other algorithms such as the MCG and the HySPADE algorithms is a key advantage of the proposed algorithms. The reduced number of operations is mainly due to the property that only a few bands are required to perform edge detection.

C. Modules

Canny Algorithm: The Canny edge detector is an edge detection algorithm that uses a multi-stage algorithm to detect a wide range of edges in images. The Canny algorithm is adaptable to various environments. Its parameters allow it to be tailored to recognition of edges of differing characteristics depending on the particular requirements of a given implementation.

Good Detection: the algorithm should mark as many real edges in the image as possible.

Good Localization: edges marked should be as close as possible to the edge in the real image.

MCG Edge Detection (Multi Color Gradient): A second approach for multicolor edge detection is to embed the variations of all color channels in a single measure, which is then used to obtain the edge maps. Typically, this approach is developed by starting from a given gray-scale operator, which is then consistently extended to multicolor images.

HySPADE Detection Algorithm: Hyper spectral imaging, like other spectral imaging, collects and processes information from across the electromagnetic spectrum. The goal of hyper spectral imaging is to obtain the spectrum for each pixel in the image of a scene, with the purpose of finding objects, identifying materials, or detecting processes.

SRC Algorithm (Spectral Ratio Contrast): Spectral Ratio Contrast (SRC) edge detection algorithm, defines the edge map of a spectral image by matching the output of the 3D mask with the ratios from the edge signature. In conjunction with a spatial mask, the few spectral bands from the edge signature give rise to a multispectral operator that can be viewed as a sparse, three-dimensional (3D) mask, which is at the heart of the two proposed edge-detection algorithms.

ASRC Algorithm (Adaptive Spectral Ratio Contrast): Adaptive Spectral Ratio Contrast (ASRC) edge detection algorithm since it adaptively changes the SRC algorithm sensitivity to edges (at each pixel) by considering the material-classification results of the neighboring pixels. The first algorithm detects edges that arise from both intensity and spectral changes while the second algorithm detects edges based on spectral changes only.

III. EXPERIMENTAL RESULTS

In our study, we employ raw HS imagery from the AHI sensor, and raw MS imagery from the DWell sensor.
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In order to create a more challenging scenario for the algorithms, we normalize the data by their broadband intensity. The normalization minimizes the role of broadband emissivity in the discrimination process and emphasizes the spectral contrast. For the AHI dataset, we only perform a qualitative comparison of the algorithms since the ground-truth information is not available for this dataset. On the other hand, for the data from the DWELL sensor we perform both qualitative and quantitative assessment of the proposed algorithms and the benchmark algorithms as the ground-truth information is available. We compare the outcome of our algorithms with the edge maps obtained by the Canny algorithm [3] (applied to selected bands), the MCG algorithm and the HySPADE algorithm. We restrict our attention to edge signatures with unity length using two bands (i.e., $S = 2$ and $R = 1$), which is the minimum value required by the algorithms. Moreover, we utilize a $3 \times 3$ spatial mask to construct the joint spatio-spectral mask, $K_{AB}$. Within the spatial mask, we identify four directions (each one associated with a pair of pixels): horizontal, vertical and the two diagonals, i.e., $M = 4$. For the ASRC algorithm, we select the distance-based Euclidean classifier for its simplicity and the good results observed; the neighborhood sets $N_{u}(i, j), N_{l}(i, j), N_{r}(i, j)$ and $N_{d}(i, j)$ are defined within the same $3 \times 3$ spatial mask used in the SRC algorithm. This choice of spatial mask, classifier and neighborhood sets is also considered for the complexity analysis.

### TABLE I: The Edge Signatures between Classes B, G and R Obtained For The AHI Data

<table>
<thead>
<tr>
<th>Signatures</th>
<th>Triplets $(p_1, q_1, p_1)$</th>
<th>Raw data</th>
<th>Normalized data</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\xi_{BG}$</td>
<td>(17, 16, 0.6941)</td>
<td>(3, 4, 0.8609)</td>
<td></td>
</tr>
<tr>
<td>$\xi_{RG}$</td>
<td>(47, 46, 0.7949)</td>
<td>(3, 4, 0.8949)</td>
<td></td>
</tr>
<tr>
<td>$\xi_{BR}$</td>
<td>(17, 16, 0.8706)</td>
<td>(16, 17, 0.9588)</td>
<td></td>
</tr>
</tbody>
</table>

### A. Edge Detection Using AHI Imagery

The AHI sensor consists of a long-wave IR (7μm-11.5μm) push broom HS imager and a visible high-resolution CCD line scan camera. The HS imager has a focal-plane array (FPA) of 256x256 elements with spectral resolution of 0.1μm. For this study, we utilize AHI data that contains three different classes: building (B), ground (G) and road (R). We utilize the 200 low-noise bands out of the 256 available bands. The calculated edge signatures (band indices and the corresponding responding ratios) for each pair of materials are summarized in Table I Fig.1 shows a comparison among the edge maps obtained by the Canny, the HySPADE, the MCG, the SRC and the ASRC algorithms for the raw sensor data (first and second columns) and for the normalized data (third and fourth columns). The Canny algorithm is applied to the same depicted image, which corresponds to the image plane at band 14. Recall that the MCG and the SRC algorithms detect edges characterized by both intensity and spectral changes. The HySPADE and ASRC algorithms, on the other hand, detect edges that exhibit a change in the spectral content only.

From the results presented in Fig.1 we observe that the Canny edge detector performs very well when applied to the AHI raw image for spectral band 14 (row I, column b). However, when the algorithm is applied to the intensity normalized image, the performance of the canny algorithm significantly degrades (row I, column d). This degradation is a result of the fact that the Canny algorithm detects intensity changes only, and it is expected to perform optimally for high intensity contrast images such as the image in row I, column a. The MCG and the SRC algorithms produce virtually the same edge maps when applied to raw sensor data (second row, columns a and b), with a clear computational advantage seen in the SRC algorithm by requiring only two spectral bands, whereas the MCG algorithm requires all the 200 available bands. When normalized data is used (second row, c and d columns), few edges in some areas are missed either by the SRC or the MCG algorithms. Nonetheless, the edge maps between the two algorithms are again comparable. Moreover, the results for the normalized case are very similar to those for the raw data case. These results show the advantage of the methods that utilize both intensity and spectral information over purely gray-scale algorithms such as Canny.
The ASRC algorithm (row III, column b) performs significantly better compared to the HySPADE algorithm (row III, column a) when applied to the AHI raw data. The edge map obtained by HySPADE exhibits noise and some of the edges that were detected by SRC, MCG and ASRC are missed by HySPADE. The advantage of ASRC over HySPADE continues to be pronounced when both algorithms are applied to the normalized data (row III, columns d and c). The edge maps obtained by the ASRC algorithm applied to raw and normalized data (row III, columns b and d) are virtually identical. This is due to the fact that the ASRC algorithm detects edges based on changes of the spectral content only. As for HySPADE, the application of the algorithm to the normalized AHI data results in a slight degradation of the edge detection but overall reduction of the noise in the edge map compared to application to the raw AHI data (row III, column a); however, as in the case of ASRC, the edge maps are comparable. It is important to note that the edge maps obtained by the MCG, the SRC and the ASRC algorithms are very similar for both raw and normalized AHI data cases. One important conclusion can be drawn from the results presented so far. By choosing only a few bands with maximum spectral separation and by allowing unrestricted band combinations to form the ratios, the SRC and ASRC algorithms (with edge signatures that use the minimal possible length) perform as well as the MCG algorithm and outperform the HySPADE algorithm. This is an important result because it lends itself to substantial data compression, compared to MCG, as well as fast processing, as compared to HySPADE. The SRC and ASRC algorithms offer a performance advantage over the Canny, the MCG and the HySPADE algorithms for images that contain isoluminant edges as seen next for the DWELL imagery.

B. Edge Detection Using DWELL Imagery

The DWELL sensor used in these experiments was designed and fabricated at the Center for High Technology Materials at the University of New Mexico. The DWELL photo detector offers a unique property of spectral tunability that is continuously controllable through the applied bias voltage. This feature of the DWELL is a result of the quantum-confined Stark effect. In essence, a single DWELL photo detector can be thought of as a continuously tunable MS spectral detector, albeit with overlapping spectral bands. In these experiments we utilize a 320×256 DWELL FPA to image two different arrangements of rocks, as shown in Fig.2 (first column). The first arrangement (top-left) is comprised of granite (G) and limestone (L) rocks (approximately 1–2 inch in diameter). The surrounding background (B) in this image corresponds to the opening of a blackbody source. The second arrangement (bottom-left) is comprised of the rocks phyllite (P), granite (G) and limestone (L), surrounded by the same background (B) as that in the first arrangement. Both examples contain an invisible isoluminant edge between the granite and the limestone rocks that exists on the tip of the black arrows.

The edge maps shown in Fig.2 were obtained by using the Sobel (second column) and the Canny (third column)

![Fig.2. Two datasets used in the current study: the first dataset is comprised of B, G and L classes (top row) and the second dataset is comprised of B, G, L and P classes (bottom row). First column: images acquired with the DWELL FPA (with enhanced contrast to show details) operating at an applied bias of 1.0V. The isoluminant edges (not visible) are marked by the tips of the black arrows. Second column: edge map obtained by the Sobel gray-scale edge detector; third column: edge map obtained by the canny gray-scale edge detector.](Image 333x256 to 576x450)

![Fig.3. Spectral response of the DWELL photo detector at an applied bias of 1.0 V.](Image 576x450 to 1152x1152)

edge detectors applied to raw DWELL-sensor data when the FPA is operated at 1.0V. The corresponding spectral response of the sensor at the applied bias of 1.0V is shown in Fig.3. Note that the Sobel edge detector has entirely missed the edge between granite and limestone rocks in both examples. Moreover, it has also failed to detect strong edges between both the granite-phyllite pair and the limestone-phyllite pair. However, the more sophisticated canny edge detector picks up these strong edges, and it partially detects the isoluminant edge in the first examples. Nevertheless, it does not detect the isoluminant edge in the second example.
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By operating the DWELL sensor at ten different bias voltages, we generated a multispectral cube to test the proposed algorithms. The obtained edge signature triplets for all the possible combinations of material pairs for both datasets are summarized in Table II. In what follows, we will term the DWELL imagery that contains background, granite and limestone classes, as shown in Fig. 2 (top-left), the first DWELL dataset, and we term the imagery that contains background, phyllite, granite and limestone, as shown in Fig.2 (bottom left), the second DWELL dataset. The results for the first DWELL dataset for raw sensor data are shown in Fig. 4. The first row of edge maps shows the results of the application of the canny edge detector to four randomly selected bands. It is important to note that some bands present a high number of false edges, whereas for other bands the isoluminant edges are detected. As such,

### TABLE II: Edge Signatures among the B, P, G, and L Classes Obtained for the Dwell Datasets

<table>
<thead>
<tr>
<th>Signature</th>
<th>Triplets (p, q, r)</th>
<th>Normalized data</th>
</tr>
</thead>
<tbody>
<tr>
<td>E_{GB}</td>
<td>(6, 7, 0.2747)</td>
<td>(10, 10, 0.1434)</td>
</tr>
<tr>
<td>E_{LB}</td>
<td>(6, 7, 0.2636)</td>
<td>(10, 10, 0.1395)</td>
</tr>
<tr>
<td>E_{LG}</td>
<td>(5, 6, 0.7577)</td>
<td>(9, 10, 0.9169)</td>
</tr>
<tr>
<td>E_{PL}</td>
<td>(4, 5, 0.5703)</td>
<td>(9, 10, 0.8444)</td>
</tr>
<tr>
<td>E_{PB}</td>
<td>(6, 7, 0.3168)</td>
<td>(10, 10, 0.2283)</td>
</tr>
<tr>
<td>E_{PG}</td>
<td>(4, 5, 0.6006)</td>
<td>(9, 10, 0.8590)</td>
</tr>
</tbody>
</table>

Fig.4. Comparison between the canny algorithms applied to individual bands (first row), MCG algorithm (second row), HySPADE algorithm (third row), SRC algorithm (fourth row) and ASRC algorithm (fifth row) for the dataset containing granite and limestone rocks (first dataset). The Canny algorithm was applied to the images at bands 1, 6, 8 and 9, respectively. The MCG and HySPADE results are presented for a sequence of increasingly permissive tolerances in order to unveil the isoluminant edge. Last two rows show the SRC and ASRC edge maps: first column, the edges E_{GB}; second column, the edges E_{LB}; third column, the edges E_{LG}; fourth column, the combined edge maps.

The Canny algorithm can generate good edge maps, depending on the bands used. The second and third rows show the results for the MCG and HySPADE algorithms, respectively, at different threshold values in order to unveil the isoluminant edge between the granite and limestone rocks. The MCG algorithm second row) picks up the weak edge only after its tolerance is increased to a degree that results in the detection of a significant number of false edges (second row, fourth column). On the other hand, HySPADE offers a less-noisy edge map compared to the MCG algorithm; nonetheless, the background-granite and granite-limestone edges are not well defined, as shown in the third row, fourth column. Moreover, the high computational cost of the HySPADE algorithm makes it hard for the user to fine tune its tolerances, which is a clear disadvantage of the HySPADE algorithm.

### TABLE III: Comparison Table for the Pd and Pf Results of Five Algorithms (Canny, MCG, HySPADE, SRC and ASRC) for the Dataset Containing B, G And L Classes (Raw Data)

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Detection probability</th>
<th>False alarm probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canny (band 9)</td>
<td>0.453</td>
<td>0.0082</td>
</tr>
<tr>
<td>MCG</td>
<td>0.9600</td>
<td>0.6112</td>
</tr>
<tr>
<td>HySPADE</td>
<td>0.7867</td>
<td>0.0565</td>
</tr>
<tr>
<td>SRC</td>
<td>0.9467</td>
<td>0.0862</td>
</tr>
<tr>
<td>ASRC</td>
<td>0.9733</td>
<td>0.0244</td>
</tr>
</tbody>
</table>

We also observe that at the cost of a slight increase in the number of false edges, the SRC algorithm can clearly define the background-granite edge with respect to the granite-limestone edge (fourth row, fourth column). Finally, the results of the ASRC algorithm (fifth row, fourth column) are better than all the previous algorithms in terms of clearly defining both the strong and weak edges. The ASRC algorithm also discards all of the false edges in the background. By utilizing the available ground-truth information for the DWELL datasets, we derived reference edge maps for the scenes under study. These edge maps are utilized to compute the empirical detection and false-alarm probabilities, P_d and P_f, respectively, for the five algorithms (Canny applied on different bands, MCG, HySPADE, SRC and ASRC). The detection probability (also known as the sensitivity of the algorithm) corresponds to the probability that an actual edge (provided by the ground truth) is detected by the algorithm under evaluation. The false-alarm probability (also known as the complement of the specificity of the algorithm) is the probability that the algorithm detects a non-existing edge. For each algorithm, we have tuned the respective parameters in order to unveil the isoluminant edges (the assessment was made by visual inspection).
We have conditioned the algorithms’ parameters to detect isoluminant edges because they present one of the most challenging problems in multicolor edge detection. The metrics $P_D$ and $P_F$ were computed by comparing the ground-truth edge-map with the algorithm outcome on a pixel-by-pixel basis. From the results presented in Table III we see that the best performance achieved by the Canny algorithm is when it is applied to band 9 ($P_D = 0.4533$ and $P_F = 0.0082$). It is important to note that the canny algorithm, applied to this band, is capable to partially detect the isoluminant edge (see Fig.4, top-right). However, without previous knowledge of the scene and the results of the application of the canny algorithm to every band, it would be difficult to guess which band gives the best results. The MCG algorithm, on the other hand, cannot detect the isoluminant edges without producing a high number of false edges. Indeed, when the isoluminant edge is detected (second row, fourth column) the MCG performance is given by a high detection ($P_D = 0.9600$) but also with a high false alarm probability ($P_F = 0.6112$). At the cost of a tremendous increase of computation complexity, the HySPADE algorithm outperforms the Canny algorithm in terms of sensitivity ($P_D = 0.7867$) and the MCG algorithm in terms of low false alarm probability ($P_F = 0.0565$). In contrast, the SRC algorithm outperforms the previous algorithms in terms of both simplicity and sensitivity with $P_D = 0.9467$, at the cost of a slight increase in the false-alarm probability ($P_F = 0.0862$) in comparison to HySPADE. The ASRC algorithm outperforms the other entire four algorithm in terms of highest detection and lowest false-alarm probability, $P_D = 0.9733$ and $P_F = 0.0244$, respectively.

![Fig.5. Comparison among the canny algorithm applied to individual bands 1, 6, 8 and 9 (first row), MCG algorithm (second row), HySPADE algorithm (third row), SRC (fourth row) and ASRC (fifth row) for the dataset containing Phyllite, Granite and Limestone rocks (second dataset). The MCG and HySPADE results are presented for a sequence of increasingly permissive tolerances in order to unveil the isoluminant edge. Last two rows show the SRC and ASRC edge maps: first column, the edges $E_{DG}$; second column, the edges $E_{PL}$; third column, the edges $E_{L4G}$; fourth column, the combined edge maps.](image)

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Detection probability</th>
<th>False alarm probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canny (band 9)</td>
<td>0.7854</td>
<td>0.0301</td>
</tr>
<tr>
<td>MCG</td>
<td>0.8802</td>
<td>0.5046</td>
</tr>
<tr>
<td>HySPADE</td>
<td>0.7445</td>
<td>0.0833</td>
</tr>
<tr>
<td>SRC</td>
<td>0.8593</td>
<td>0.0873</td>
</tr>
<tr>
<td>ASRC</td>
<td>0.8919</td>
<td>0.0652</td>
</tr>
</tbody>
</table>

The edge-detection results for the second DWELL dataset are presented in Fig.5 for intensity-normalized data. Table IV summarizes the detection and false-alarm probabilities achieved by each one of the five algorithms for this dataset. The second dataset is more challenging than the first dataset because the two classes with the isoluminant edge (i.e., granite and limestone rocks) are now positioned against a phyllite background that exhibits less contrast than the blackbody. Moreover, the data is intensity normalized. As before, the canny edge detector achieves good performance when applied to band 9 ($P_D = 0.7854$ and $P_F = 0.0301$). It is very interesting to note that (for this band) the canny algorithm is capable detecting the isoluminant edge between the granite and limestone rocks almost fully. This is because the normalization process smooths some intensity peaks and improves the contrast between granite and limestone (for this particular band) as a secondary effect. This result proves that the first category of algorithms (those that do not use spectral information) can achieve good detection as long as the best band is identified through pre-processing of the data, which can be a very difficult requirement.

As for the MCG-generated edge maps, Fig.5 (second row), the weak edge is detected only when the false-alarm probability reaches unacceptable levels. The HySPADE algorithm performs worst than the MCG algorithm ($P_D = 0.7445$ and $P_F = 0.0833$) and it is not capable of detecting the isoluminant edge. In contrast, the SRC algorithm recovers the strong edges as well as the weak edge between the granite and limestone rocks. Indeed, Fig.5 (fourth row) shows a high-resolution weak edge captured by the SRC algorithm. The achieved detection and false-alarm probabilities of the SRC algorithm ($P_D = 0.8593$ and $P_F = 0.0873$) corroborate this observation. It is important to note that even though the SRC algorithm is able to detect isoluminant edges for challenging scenarios, it still suffers from detecting false edges for each pair of materials, as observed in both examples. However, the ASRC algorithm
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reduces the detection of false edges substantially ($P_F = 0.0652$ for ASRC compared to $P_F = 0.0873$ for SRC), owing to the fusion of material classification in the edge-detection process. The ASRC is also able to improve the detection of edges, as noted by the improved detection probability ($P_D = 0.8919$ for ASRC compared to $P_D = 0.8593$ for SRC). From these results, we can conclude that the SRC algorithm outperforms the MCG and HySPADE algorithms for the task of detecting edges using spectral data with minimal intensity contrast. Moreover, it performs as good as the canny edge detector without the difficult requirement for pre-selecting the optimal band. Moreover, at the cost of a slight increase in computational cost, the ASRC algorithm outperforms all other four algorithms presented in this paper. Next, we compare the multicolor algorithms (SRC, ASRC, MCG and HySPADE) in terms of their computational costs.

IV. CONCLUSION

We have described a procedure for the design of edge detectors for arbitrary edge profiles. The design was based on the specification of detection and localization criteria in a mathematical form. It was necessary to augment the original two criteria with a multiple response measure in order to fully capture the intuition of good detection. A mathematical form for the criteria was presented, and numerical optimization was used to find optimal operators for roof and ridge edges. The analysis was then restricted to consideration of optimal operators for step edges. The result was a class of operators related by spatial scaling. There was a direct tradeoff in detection performance versus localization, and this was determined by the spatial width. The impulse response of the optimal step edge operator was shown to approximate the first derivative of a Gaussian. The ASRC algorithm is a specialized version of the SRC algorithm, aimed at detecting edges that are due to a change in the material only. The ASRC aims to reduce the detection of false edges due to unwanted changes in the intensity. Among the possible extensions of the work, the most interesting unsolved problem is the integration of different edge detector outputs into a single description. A scheme which combined the edge and ridge detector outputs using feature synthesis was implemented, but the results were inconclusive. The problem is much more complicated here than for edge operators at different scales because there is no clear reason to prefer one edge type over another. Each edge set must be synthesized from the other, without a bias caused by overestimation in one direction. In particular, this band-reduction feature is particularly relevant to emerging spectral imaging sensors that are bias tunable, such as the DWELL sensor, where one can perform intelligent acquisition by programming the sensor electronically to sense only at the few prescribed bands.

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